A PHYSICS-BASED FAST-RUNNING SURROGATE MODEL FOR CRASH PULSE PREDICTION

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ABSTRACT

Recent developments in safety performance assessment of safety technologies by virtual simulation show a trend towards scenario-based approaches, especially for pre-crash technologies and driving automation systems. The models used for such types of simulations are rather fast, so many simulations can be performed in reasonable time. However, if the application of scenario-based approaches is extended to in-crash occupant protection technologies, finite element (FE) crash models come into play for e.g., determining the crash pulse. These models are very time-consuming and not suited for performing large-scale studies. The research objective therefore was to develop a model that delivers sufficiently accurate estimations of the crash-pulse in a frontal impact depending on crash configuration parameters while being fast enough to be used in large-scale safety performance assessment studies.

We built a multi-body-system (MBS) model consisting of the main frontal crash relevant structural elements (crash boxes, longitudinal member, cross member, engine, firewall) as well as the rest of the vehicle (passenger cabin and luggage trunk), which is modelled as one rigid body. Nonlinear force elements are used to model the elastic and plastic deformations. We optimized the parameters of the force elements by using results of 96 FE simulations of a high-fidelity full vehicle model impacting a rigid barrier. In those 96 simulations, we varied the impact speed, impact angle and lateral offset.

The physics-based surrogate model provides translational and rotational accelerations, speeds, and positions over time. The results show a good correlation to the results of the high-fidelity model: the mean absolute occupant load criterion (OLC) error for all 96 crash configurations is 0.88 g. The physics-based surrogate model needs less than one second for one run of 200 milliseconds on 1 CPU while the high-fidelity FE model needs more than 15 hours on 16 CPUs for the same task.

The model can be used to predict crash-pulses in the range of crash configuration parameters it was optimized for. It can be extended to other crash configurations. Its parameters can be adapted to represent other vehicles by adapting physical parameters like mass, lengths etc. due to the physics-based approach. This is a major advantage compared to non-physics-based black-box surrogate modelling techniques used for the same purpose, where the internal parameters do not represent any physical property. Moreover, the physics-based surrogate model can also be used to simulate a crash between two vehicles (even with different properties) by using another model instance instead of a rigid barrier as opponent. The model delivers an estimation of the crash-pulse, so its main purpose is to be used in large-scale studies, not to exactly reproduce one singular case. So far it can only be used in frontal crashes, but it could be extended for rear-end crashes as well by adding the respective structures at the rear end.

The model developed can predict crash-parameter-dependent crash-pulses and can be an essential part in accelerating large-scale safety performance assessment studies of occupant protection systems in frontal crashes.

RESEARCH QUESTION / OBJECTIVE

Two major trends currently emerge in vehicle safety system development. The first trend is related to the types of safety systems. While in-crash related safety measures (often called passive safety systems) are already quite long in the market and also systems operating in the pre-crash phase (often called active safety systems) are state of the art, the fusion of both types of systems into integrated safety is rather new.

The second trend is related to the virtual, simulation-based performance assessment of safety systems. Here scenario-based virtual testing methods are more and more used. These methods try to cover a wider range of possible scenarios that a certain safety system might encounter in real-world application. The first trend leads to the requirement of combining pre- and in-crash simulation. This in combination with the large number of simulation runs required for scenario-based testing leads to the need for fast in-crash models in order to be able to perform studies in reasonable time.

When looking at occupant protection, one essential element in assessing the performance of an integrated safety system is the determination of the resulting crash pulse in dependence of the involved vehicles and the crash configuration. A crash pulse prediction model suitable for scenario-based safety performance assessment therefore must fulfil the following requirements:

- The model should run fast. This is the basic requirement for a model to be included in large-scale studies. High-fidelity finite element (FE) models of the vehicle structure, a classical approach for determining crash pulses don't fulfil this requirement, as they typically take several hours to complete one crash simulation.
- The model should provide crash pulses at least in vehicle longitudinal direction but preferably also in lateral direction as well as around the yaw axis.
- The model should be applicable for a given range of crash configurations defined by impact speed, lateral offset and impact angle.
- The model should represent a two-vehicle crash, ideally with the possibility of using a configuration with two different vehicles.

The research objective therefore can be summarized as follows: development of a model that delivers sufficiently accurate estimations of the crash-pulse in a frontal impact depending on crash configuration parameters while being fast enough to be used in large-scale safety performance assessment studies.

METHOD

Several approaches were published for similar applications. [1] not only presents one concrete solution but also a summary of surrogate modelling approaches. Two main branches for surrogate modelling can be distinguished:

- Mathematical / black-box surrogate models which do not have a physics-based relation between in- and outputs. Various methods exist, see [1], (e.g. OSCCAR). These models are very flexible in terms of application, but they rely heavily on data for model training. As the relation between in- and outputs is usually not connected to physical parameters of the system that should be replaced, it is not possible to adapt such models to even slight differences in physical properties, like vehicle mass etc. The only possibility to enable consideration of such parameters is extending the reference data respectively.
- Physical /simplified surrogate models which model the mechanical behaviour of the vehicle during crash, but in a simplified way compared to high-fidelity FE models. Many approaches exist according to [1], most of them use FE or multi-body-system (MBS) methods but with simplifications in one or the other way.

We decided to use an MBS approach for the surrogate model as it is fast and has parameters that directly represent mechanical properties of the substituted vehicle(s). Moreover, we are mostly interested in the crash pulse, not the detailed deformation of the structure itself. The rest of this section is divided in three parts. The first part is about how we set-up the model. The second part is about generating reference data to which the new model can be fitted and compared to. The third part describes the fitting process.

Set-up of MBS model

Multi-body-systems consist of rigid bodies, joints that connect these bodies and force elements that apply forces between two bodies or between one body and the ground (the fixed reference for the model). Another way of interaction between bodies is contact between bodies. The resulting normal contact force usually depends on the intrusion and intrusion velocity, the tangential force on the defined friction coefficient.

We used the software PyBullet [2] to set up the model. PyBullet is a physics engine primarily developed to be used for robotics simulation and machine learning. It provides amongst other features forward dynamics simulation and collision detection and handling. It runs on Windows and Linux. We chose this software because it provides all required features, is fast, and multiple model instances can be used in parallel which increases performance even more. It is available under the zlib license.

The model consists of several bodies, joints, and force elements. The root body (grey box in the right part of **Figure 1**) represents the rear part of the vehicle, i.e., everything behind the firewall. Only one body is used for this part as no deformation is expected to happen here in a frontal impact. The longitudinal members (green boxes in **Figure 1**) are mounted to this root body using a combination of revolute joint (rotation axis z global) and prismatic joint (along the longitudinal axis). Parallel to the prismatic joint we added a force element which models the deformation behaviour of the longitudinal member. The lateral bending behaviour is covered by the revolute joint. The crash boxes (blue boxes in **Figure 1**) are connected via a prismatic joint allowing translation along the longitudinal axis (x-global direction in undeformed state). Again, we added a force element parallel to the prismatic joint which models the deformation behaviour of the crash box. The cross member (black box in **Figure 1**) is divided into two parts so that the cross member can also be deformed during impact. The two cross member parts are connected to the respective crash boxes via a revolute joint (rotation axis z global). Connecting the two cross members via a joint would result in a loop structure, which is not allowed in PyBullet. To create a loop structure, constraints must be used instead of joints. So, we used a prismatic constraint to connect the two cross member parts. The engine is connected to the root body using a planar joint that allows movement in the global x-y plane and with two constraints (point-to-point) to both longitudinal members. A schematic of the model can be found in **Figure 2**.

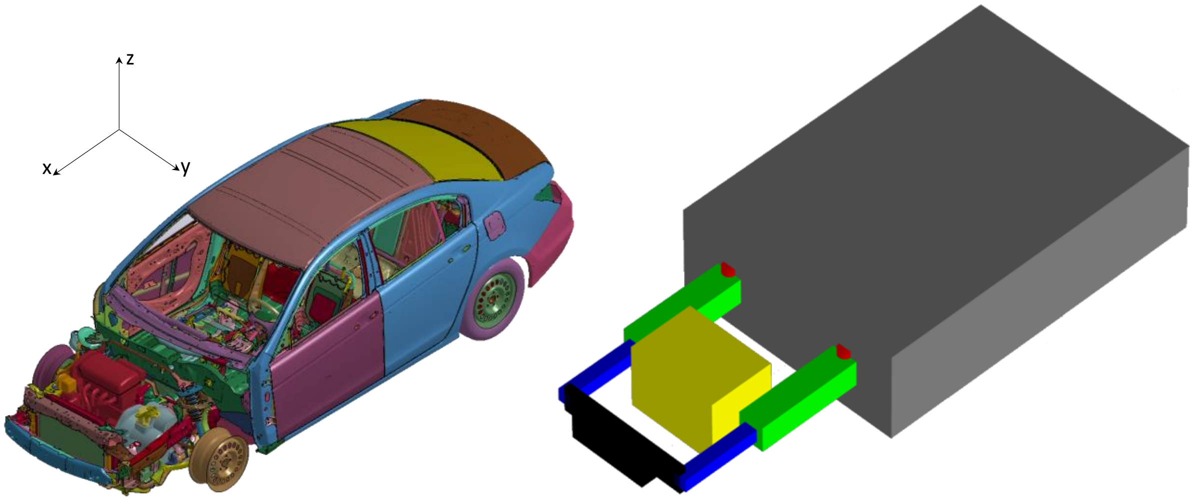

Figure 1. Left: The FE model to be replaced (some parts in front are removed to make the relevant structural elements visible). Right: The surrogate MBS model.

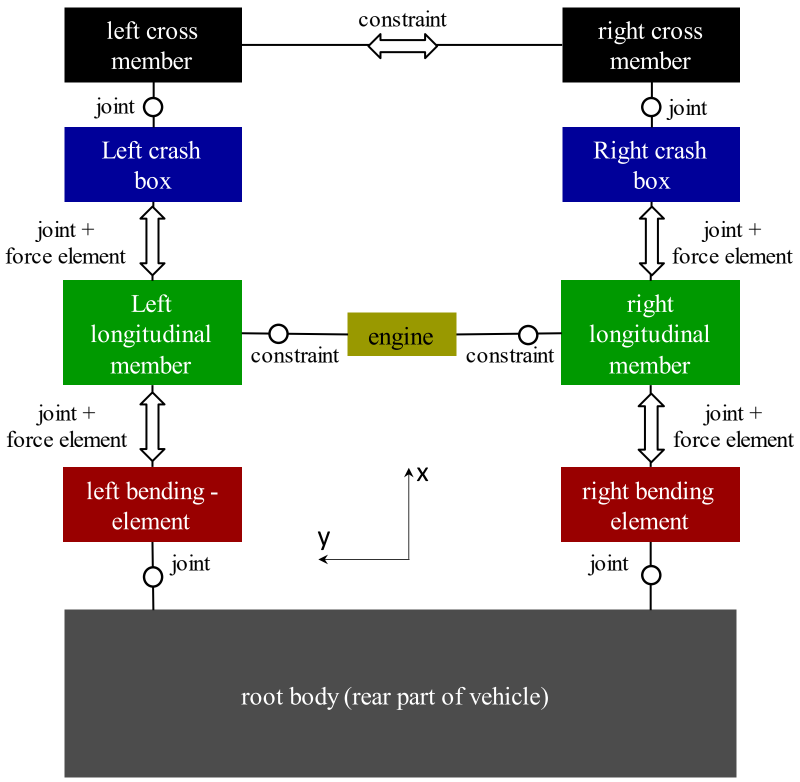

Figure 2. Schematic of the MBS model.

The force elements parallel to the prismatic joints use a characteristic as shown in **Figure 3**: The force raises linearly until a force level is reached where the collapsing of the structure begins (Point $s_{collapsing\ begin}$ / $F_{collapsing\ begin}$ in **Figure 3**). This phase is followed by a phase where the longitudinal members and crash boxes continue to collapse until the point is reached, where no more significant plastic deformation is possible (Point $s_{collapsing\ end}$ / $F_{collapsing\ end}$ in **Figure 3**). From this point on the structure is assumed to not deform any more. The unloading is done using a linear characteristic.

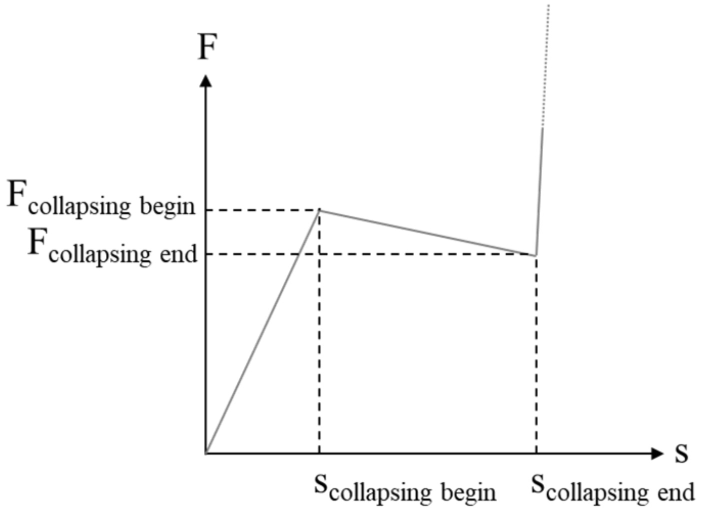

Figure 3. The displacement-force characteristics of the force elements.

The opponent in the crash simulation for the steps described in the following is a rigid barrier (modelled as one rigid body), but it is also possible to use two MBS-models colliding with each other in an oncoming crash configuration.

Generation of reference data

Now that the model is set up, model parameter values need to be defined. Some of them can be determined directly based on the information about the substituted vehicle model, like masses, positions, and dimensions of crash-relevant structures. Others, especially parameters defining the force elements cannot be derived directly but must be obtained differently. We used a model parameter optimization approach to fit those parameters so that the surrogate model output gets as close as possible to the output of the substituted vehicle model. To do so, we need reference data (as set of input data and related output data) to fit the surrogate model to.

The reference data is generated by performing simulations with the FE model for defined parameter sets. We chose three parameters that define the crash configuration: impact speed, lateral offset between vehicle and rigid barrier and impact angle. The speed values used are: 25, 35, 45, and 56 km/h. The lateral offset ranges from -1050 to + 1050 mm in 350 mm increments. The impact angle ranges from 0 to 30° in 10° steps. We did a full factorial experiment design resulting in 4 speeds x 7 lateral offsets x 4 angles = 112 parameter combinations.

We used the freely available and validated Honda Accord (model year 2014) FE model [3] and added the rigid barrier as crash opponent. The simulations were performed using LS-Dyna, version 9.2.

The outputs of the simulations are the resulting accelerations, velocities, and displacements in x-, y-, and z-direction over time in the vehicle's centre of gravity. These will be used as reference data for the parameter optimization process described next.

Model parameter optimization

As mentioned above, some of the parameters cannot be derived directly from the original model but must be determined otherwise. We used optimization to find an optimal set of parameters that makes the surrogate model results fit to the FE model results as closely as possible.

As the number of parameters is large and it is not known whether there is only one optimal solution, we used in the first step a global optimisation method, more specifically a differential evolution algorithm implemented in the python package inspyred, version 1.0 [4]. In a follow-up step, we used a local optimisation method (Nelder-Mead algorithm implemented in the python package scipy, version 1.7.3, [5]) to find the final, optimal set of parameters. The quality criterion for the optimization process is based on the mean absolute error (MAE):

$$MAE = \frac{\sum_{i=1}^{n} \left| y_{pred,i} - y_{true,i} \right|}{n} \quad (1)$$

with y_{pred} as the value predicted by the surrogate model, y_{true} as the FE model result and n as the total number of values. The value to be minimized is a sum of five MAE values (for the rest of the paper referred to as "total error"): the MAE of the acceleration over time in x- and y-direction, the MAE of the velocity over time in x- and y-direction and the MAE of the instant in time where the velocity in x-direction reaches zero. We weighted both velocity MAEs with a factor of ten as we see this as the most important element in the optimization process. Moreover, each function call of the optimization process uses simulations of 96 of the 112 possible parameter combinations to cover the whole range of crash configurations the surrogate model should be used for. The reasons for using only 96 of 112 possible combinations are:

- The combination of an impact angle of 30° and a lateral offset of 1050 mm results in a crash configuration where the rigid barrier misses the crash box and the longitudinal member. This case cannot be covered by the MBS model. This reduces then number of combinations by 4 to 108.
- As the MBS model is symmetric about the x-axis, variations of lateral offset with same absolute value but different sign and an impact angle of zero degrees result in similar results. For those cases, the average of both results of the FE model are used. This further reduces the number of combinations by 12 to 96.

The optimization process resulted in a set of parameters which provides the results shown in the next section.

RESULTS

This section is divided into three parts. First, the results of the optimization process are presented, focussing on the model quality criteria used during the process itself. The second part focuses on the output of the models in terms of occupant load criterion (OLC), the third and final part is about calculation time.

Optimization process results

Figure 4 shows the cumulative density of the total error, MAE for longitudinal acceleration and longitudinal velocity. More than 50% of all parameter combinations result in a MAE for longitudinal acceleration of lower than 1 g and in a MAE for longitudinal velocity of lower than 2 m/s. More than 75 % of all parameter combinations result in a MAE for longitudinal acceleration of lower than 2 g and in a MAE for longitudinal velocity of lower than 3 m/s.

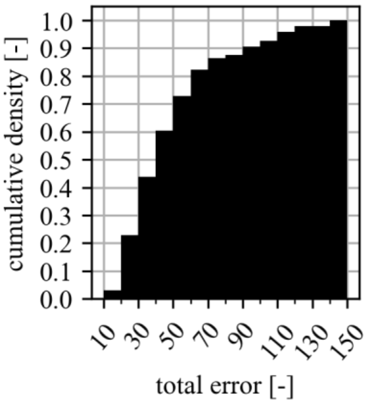

Figure 4. Cumulative density of total error (left), MAE for longitudinal acceleration (middle), and MAE for longitudinal velocity (right).

It is also of interest how much the results vary depending on the parameters describing the crash configuration. **Figure 5** therefore shows the mean values of the total error in dependence of speed, lateral offset and angle. It can be seen that the the total error increases with increasing speed and stays on the same level for angle variations. The variation of offset shows an outlier towards higher total error at 1050 mm.

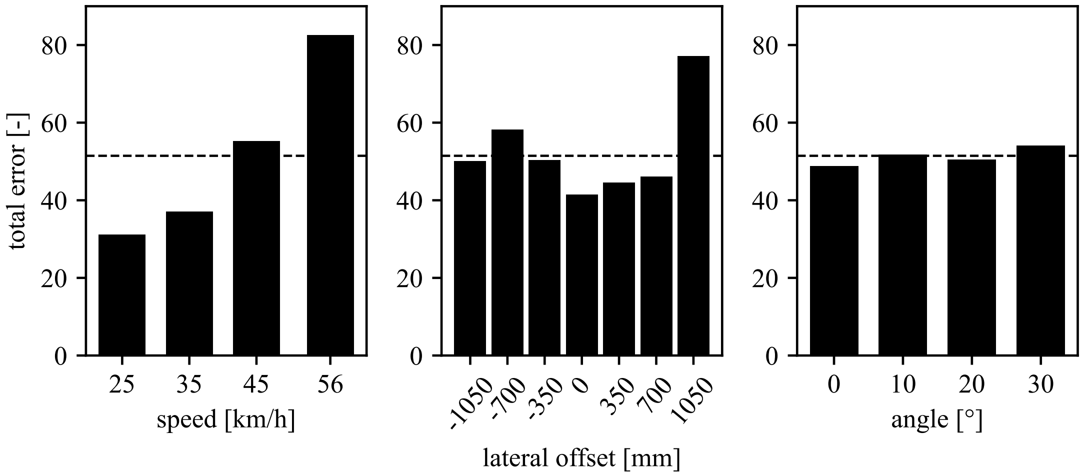

Figure 5. Mean values of total error in dependence of speed (left), lateral offset (middle) and angle (right). The horizontal dashed line indicates the mean total error of all runs.

Figure 6 shows the simulation set-ups for this lateral offset. These are configurations where the vehicle might stick to the rigid barrier and bounce back or slide laterally off the rounded corner of the rigid barrier and continue moving forward. Depending on what happens, the resulting accelerations, velocities etc. will differ significantly. Different behaviour of FE and MBS model in some of these situations is one reason for the large errors in these cases. Another reason is that even if both models behave the same, the sliding off happens in a different way in both models, also resulting in larger differences than in other configurations where this effect does not occur.

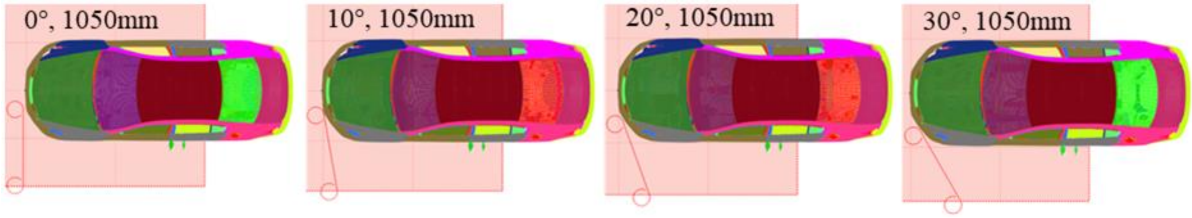

Figure 6. Simulation set-ups for lateral offset of 1050 mm and varying angle (0°, 10°, 20°, and 40°).

Figure 7 shows the time histories for longitudinal acceleration, velocity, and displacement as well as longitudinal acceleration over displacement for the parameter combinations resulting in lowest and highest total error. At the left side (best result) a very good correlation especially in terms of velocity and in the instant in time where the velocity in x-direction reaches zero can be seen. At the right side (worst result), the longitudinal velocity and displacements start to deviate at about 0.75 s. The reason for that is the same as mentioned above (sliding off the rounded corner) and shown in **Figure 8**: If the animations of both simulations for that parameter combination are laid on top of each other, it can be seen that the MBS model slides laterally off the rounded corner of the rigid barrier resulting and continues moving forward while the FE model sticks to the wall and bounces back instead of sliding off.

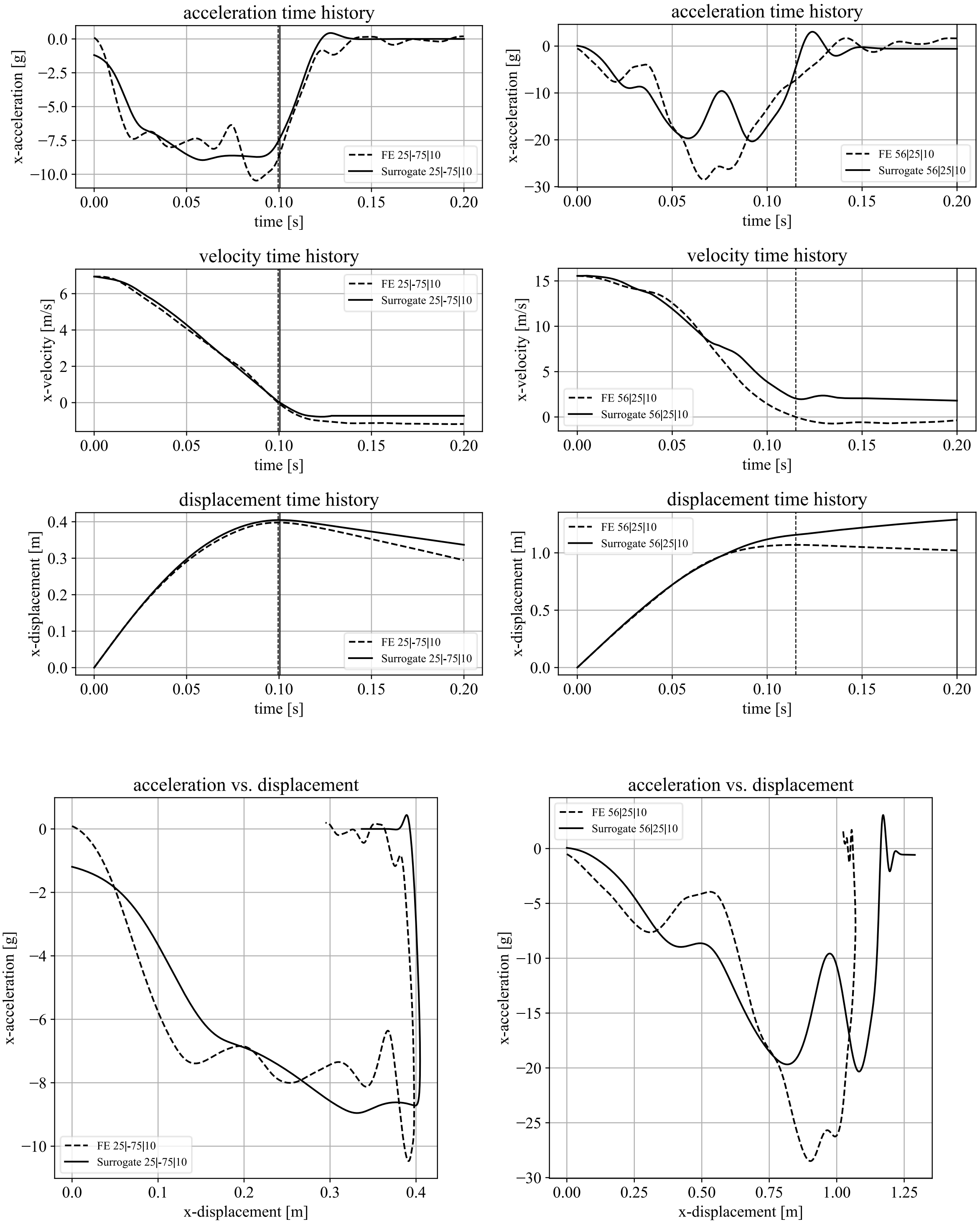

Figure 7. Results for the crash configurations resulting in lowest (left) and highest (right) total error.

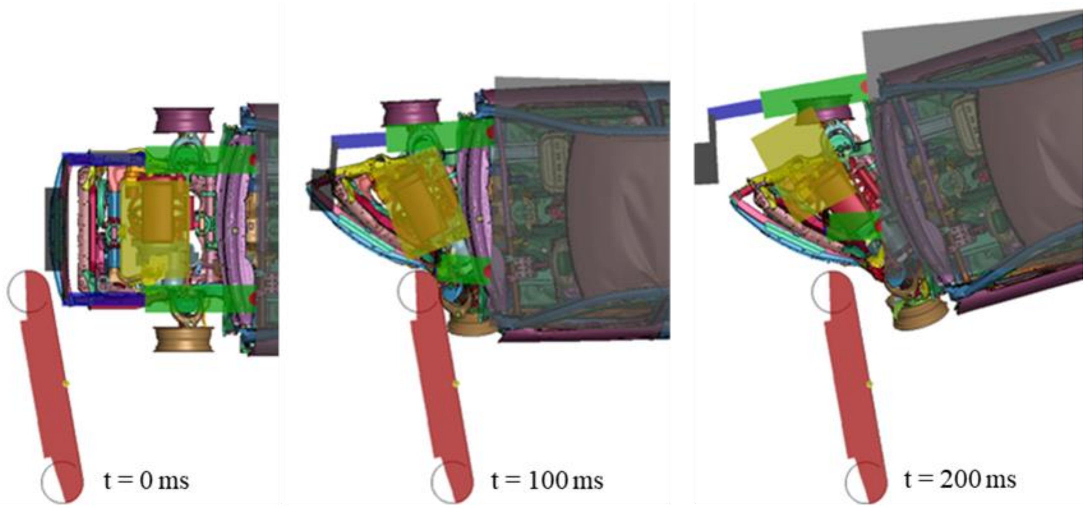

Figure 8. Overlay (top view) of simulation visualization at 0 milliseconds (left) 100 milliseconds (middle) and 200 milliseconds (right) for the parameter combination resulting in the worst model quality value.

Occupant load criterion-based analysis

The metrics used in the optimization process are suitable for assessing the similarity of the mechanical behaviour of FE and MBS model. However, they are less suitable to predict the model quality in terms of similarity in resulting occupant injury severity. We therefore did a second comparison of FE and MBS model using the occupant load criterion (OLC) [6] as it shows a good correlation to the crash pulse severity [7].

The OLC error (defined as difference between OLC calculated from MBS model output and OLC calculated from FE model output) ranges from -5.45 g to 2.38 g. As we are rather interested in the absolute deviation of the two values, we use the absolute value of the OLC error further on. The mean value of the absolute OLC error is 0.88 g, the 25th percentile value is 0.29g, the 50th percentile value is 0.62 g, and the 75th percentile value is 1.13g. **Figure 9** shows the cumulative density of the absolute OLC error.

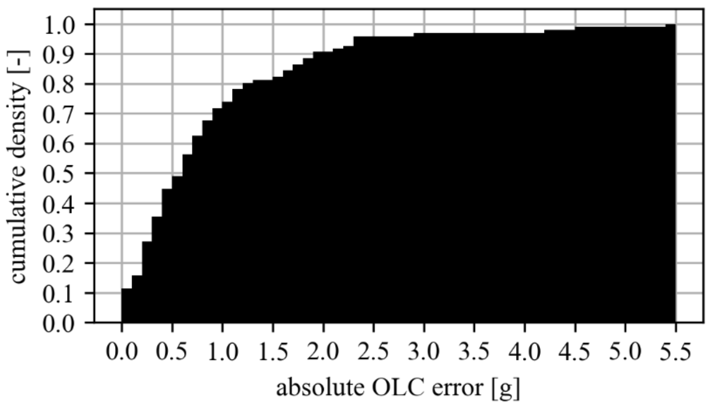

Figure 9. Cumulative density of the absolute OLC error.

As before, also the dependence of the absolute OLC errors on the parameters describing the crash configuration are analyzed, see **Figure 10**. Again, the largest spread is found at the speed variation while the variation in angle results in the smallest spread.

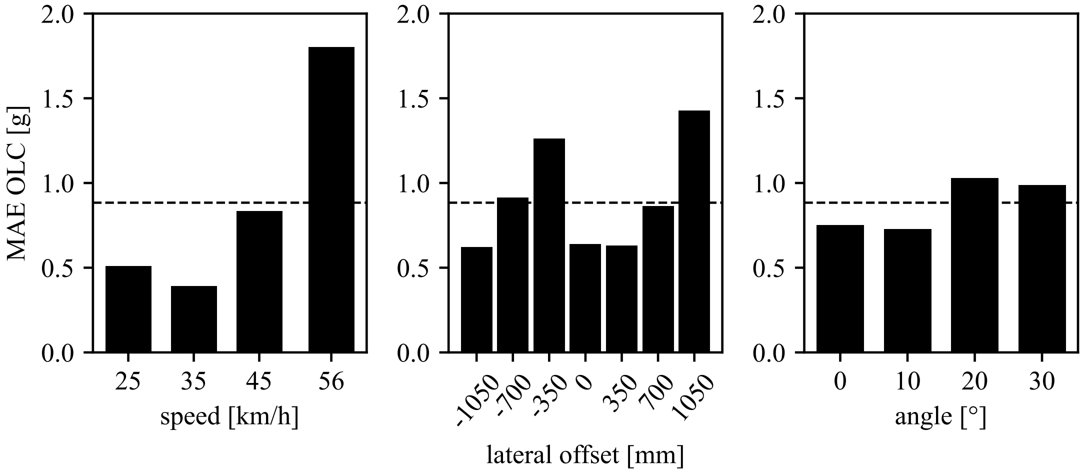

Figure 10. Mean values of absolute OLC errors in dependence of speed (left), lateral offset (middle) and angle (right). The horizontal dashed line indicates the mean of the absolute OLC errors of all runs.

OLC results for all parameter combinations can be found in the appendix in **Table 1**, **Table 2**, **Table 3**, and **Table 4**.

Calculation time

The FE model simulation takes on average 15 hours on 16 CPUs for one run of 200 milliseconds of simulated time. In comparison, the surrogate model takes on average 0.4 seconds on one CPU for one run of 200 milliseconds of simulated time.

Application in car-to-car crash

Instead of using a rigid barrier as opponent, the MBS model can also be set-up with two instances of the vehicle model thus representing a car-to-car crash. To check, whether this set-up also works, we set up a frontal collision case with two vehicles approaching each other with 56 km/h, 0 mm lateral offset and an angle of 0°. This setup should provide the same results compared to the rigid barrier case with 56 km/h. **Figure 11** shows the two set-ups. **Figure 12** shows the vehicle's centre of gravity time histories for longitudinal acceleration, velocity, and displacement as well as longitudinal acceleration over displacement for FE model and both MBS model set-ups.

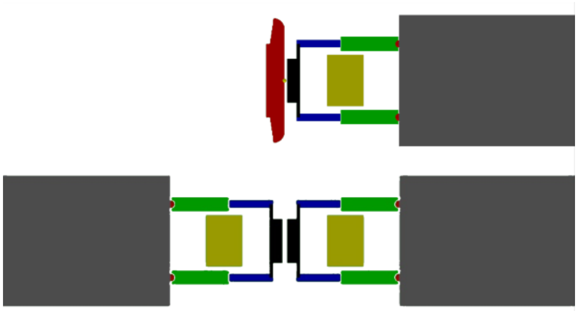

Figure 11. MBS model set-up for a lateral offset of 0 mm and angle 0° using as opponent a rigid barrier (top) or a second instance of the vehicle model (bottom).

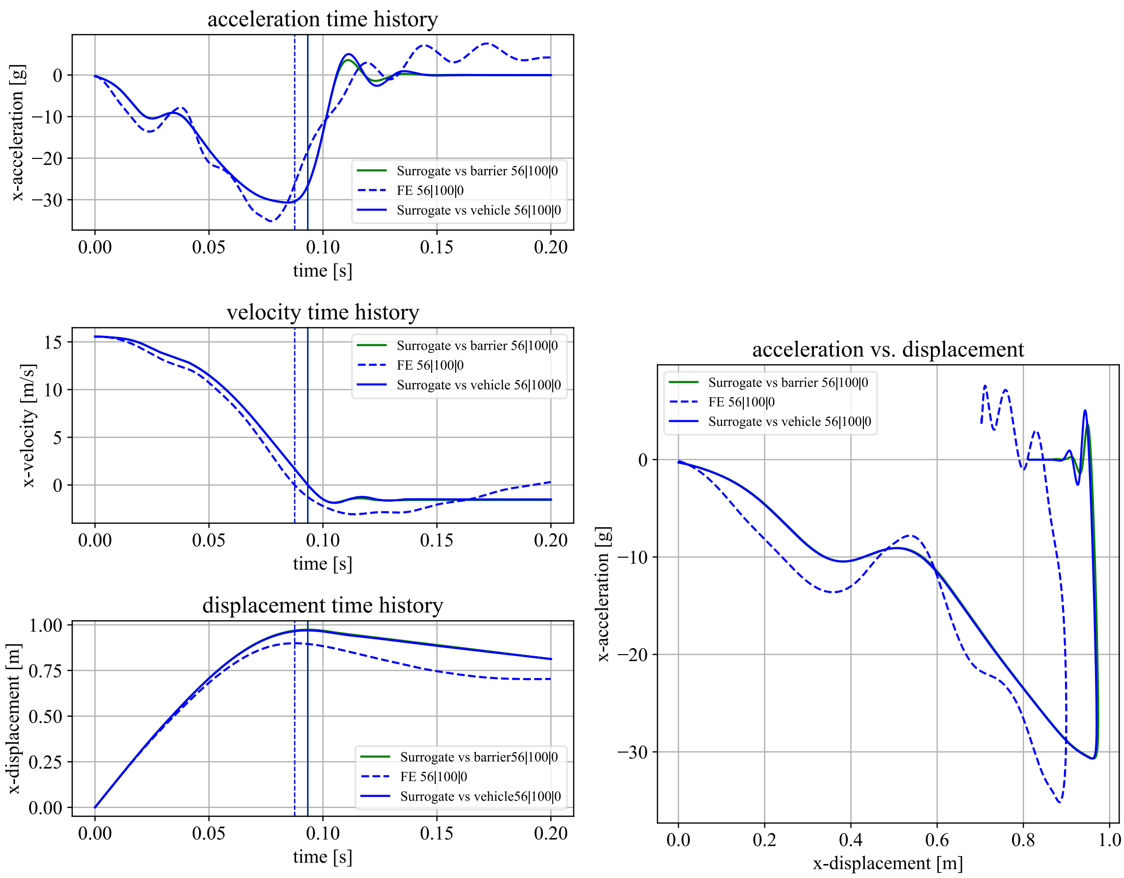

Figure 12. Comparison of results for FE-model, MBS model using as opponent a rigid barrier or a second instance of the vehicle model.

DISCUSSION AND LIMITATIONS

The surrogate model can be used to predict crash-pulses in the range of crash configuration parameters it was optimized for. The results, especially in terms of OLC error, show that most of the surrogate model's outputs are close to the ones of the FE model. With higher impact speeds, the total error and the MAE of the OLC increases. This can be expected, as higher impact speeds mean higher levels of all output quantities and the comparisons are made on absolute values, not relative ones. The model quality is less sensitive to variations in angle. When looking at specific crash configurations, larger deviations can be seen. One such group of configurations with larger deviations are the ones where the vehicle could slide off the rounded corner of the rigid barrier. However, these cases are less relevant for the practical application, as this sliding off will not happen in a similar way in car-to-car crash configurations. A possibility would be to explicitly exclude such configurations from the surrogate model's validity range, i.e., not use it for such configurations. Moreover, the surrogate model was developed to be used in large-scale studies and produce a large number of crash pulses which in total are representative and not to exactly reproduce one singular case.

The surrogate model is fast enough for such large-scale studies, even when used as single instance. As multiple instances can run in parallel, the performance in terms of simulation time can be increased even more.

The chosen, physics-based approach has two major advantages compared to non-physics-based black-box surrogate modelling techniques used for the same purpose:

- The surrogate model can be extended to be applicable for other crash configurations. So far it can only be used in frontal crashes, but by adding the respective structures at the rear end it can also be used for rear-end crashes

- The surrogate model can represent other vehicles by adapting physical parameters like mass, lengths etc. while this is not possible for a black-box model as its internal parameters do not represent any physical property.

Moreover, the physics-based surrogate model can also be used to simulate a crash between two vehicles (even with different properties) by using another vehicle model instance instead of the rigid barrier as opponent. The resulting curves for the case to check this possibility are almost identical, slight differences appear only in the rebound phase (see **Figure 12**).

CONCLUSIONS

The surrogate model developed extends the possibilities of scenario-based large-scale safety performance assessment studies to also consider the influences of the mechanical in-crash vehicle behaviour on occupants. With a simulation time of 0.4 seconds for 200 milliseconds simulated time, the surrogate model is fast enough for such types of studies. The model provides crash pulses in longitudinal and lateral direction. It is suitable to be used in the most relevant frontal crash configurations in terms of impact speed, angle and lateral offset. Although the surrogate model was set-up using a rigid barrier as crash opponent, it is also suitable for car-to-car frontal crashes by using two instances of the vehicle model. The two vehicles could even have differing physical properties like mass, lengths etc. Future work might include extending the range of application for frontal crash configurations or even going further by extending the surrogate model so that it can be used in totally different crash configurations like side or rear-end impact. The application of this modelling approach can be an essential part in accelerating large-scale safety performance assessment studies of occupant protection systems in frontal crashes.

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APPENDICES

Table 1.

OLC results for 25 km/h

Velocity [km/h]	**Lateral offset [mm]**	**Angle [°]**	**OLC_{FE}**	**OLC_{MBS}**	**OLC error**
25	-350	10	8.42	8.39	-0.03
25	-350	20	8.25	7.72	-0.53
25	-350	30	5.89	6.39	0.5
25	-700	10	8.45	8.5	0.05
25	-700	20	8.46	8.23	-0.23
25	-700	30	7.87	7.16	-0.71
25	-1050	10	6.67	7.14	0.47
25	-1050	20	7.82	8.48	0.66
25	-1050	30	8.01	8.36	0.35
25	1050	0	6.92	5.9	-1.02
25	1050	10	7.67	6.96	-0.71
25	1050	20	2.37	4.75	2.38
25	700	0	8.15	8.39	0.24
25	700	10	7.82	8.07	0.25
25	700	20	7.29	6.79	-0.5
25	700	30	5.72	6.21	0.49
25	350	0	9.27	8.4	-0.87
25	350	10	8.37	8.4	0.03
25	350	20	7.96	7.72	-0.24
25	350	30	6.2	6.21	0.01
25	0	0	9.37	8.38	-0.99
25	0	10	8.39	8.4	0.01
25	0	20	8.08	7.72	-0.36
25	0	30	5.82	6.39	0.57

Table 2.

OLC results for 35 km/h

Velocity [km/h]	**Lateral offset [mm]**	**Angle [°]**	**OLC_{FE}**	**OLC_{MBS}**	**OLC error**
35	-350	10	11.83	11.73	-0.1
35	-350	20	11.44	11.17	-0.27
35	-350	30	9.8	9.59	-0.21
35	-700	10	12.07	11.76	-0.31
35	-700	20	11.73	11.65	-0.08
35	-700	30	11.44	10.27	-1.17
35	-1050	10	11.05	11.11	0.06
35	-1050	20	12.18	11.76	-0.42
35	-1050	30	12.14	11.77	-0.37
35	1050	0	11.3	10.47	-0.83
35	1050	10	10.92	10.12	-0.8

35	1050	20	5.4	6.59	1.19
35	700	0	11.92	11.72	-0.2
35	700	10	11.64	11.35	-0.29
35	700	20	10.67	10.25	-0.42
35	700	30	8.82	8.16	-0.66
35	350	0	11.89	11.72	-0.17
35	350	10	11.94	11.73	-0.21
35	350	20	11.15	11.17	0.02
35	350	30	9.66	9	-0.66
35	0	0	12.12	11.72	-0.4
35	0	10	12.14	11.73	-0.41
35	0	20	11.28	11.17	-0.11
35	0	30	9.62	9.59	-0.03

Table 3.

OLC results for 45 km/h

Velocity [km/h]	Lateral offset [mm]	Angle [°]	OLC_{FE}	OLC_{MBS}	OLC error
45	-350	10	16.67	17.33	0.66
45	-350	20	17.56	16.45	-1.11
45	-350	30	16.34	14.54	-1.8
45	-700	10	19.3	17.71	-1.59
45	-700	20	16.64	17.39	0.75
45	-700	30	15.94	14.57	-1.37
45	-1050	10	16.95	17.23	0.28
45	-1050	20	18.6	17.8	-0.8
45	-1050	30	17.17	17.88	0.71
45	1050	0	15.7	15.7	0
45	1050	10	15.27	13.61	-1.66
45	1050	20	8.82	9.99	1.17
45	700	0	17.38	17.78	0.4
45	700	10	16.02	16.98	0.96
45	700	20	16.19	15.51	-0.68
45	700	30	12.34	11.08	-1.26
45	350	0	16.89	17.8	0.91
45	350	10	16.29	17.33	1.04
45	350	20	16.83	16.44	-0.39
45	350	30	14.52	14.04	-0.48
45	0	0	17.07	17.81	0.74
45	0	10	17.03	17.33	0.3
45	0	20	17.07	16.46	-0.61
45	0	30	14.94	14.57	-0.37

Table 4.

OLC results for 56 km/h

Velocity [km/h]	Lateral offset [mm]	Angle [°]	OLC_{FE}	OLC_{MBS}	OLC error
56	-350	10	24.27	24.02	-0.25
56	-350	20	26.21	21.97	-4.24
56	-350	30	25.9	20.45	-5.45
56	-700	10	26.69	25.03	-1.66

56	-700	20	25.12	23.31	-1.81
56	-700	30	21.71	20.47	-1.24
56	-1050	10	22.72	21.92	-0.8
56	-1050	20	27.06	25.15	-1.91
56	-1050	30	25.95	25.33	-0.62
56	1050	0	22.18	19.81	-2.37
56	1050	10	22.47	17.94	-4.53
56	1050	20	12.65	13.1	0.45
56	700	0	27.44	25.16	-2.28
56	700	10	23.76	23.45	-0.31
56	700	20	23.01	20.07	-2.94
56	700	30	15.9	13.95	-1.95
56	350	0	24.78	25.21	0.43
56	350	10	24.81	23.99	-0.82
56	350	20	24.03	21.93	-2.1
56	350	30	20.59	18.87	-1.72
56	0	0	25.4	25.21	-0.19
56	0	10	25.74	23.96	-1.78
56	0	20	24.35	21.96	-2.39
56	0	30	21.39	20.42	-0.97